HOTEL RECOMMENDATION BOOKING PREDICTION USING MACHINE LEARNING

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Abstract **- Accurate prediction of hotel booking cancellations is crucial for improving revenue management and operational efficiency in the hospitality industry. With the advancement of machine learning (ML), it is now possible to predict cancellations based on historical booking data and customer behavior patterns. This research explores the application of ML algorithms to forecast booking cancellations using real-world hotel datasets. The aim is to help hotel managers minimize losses from last-minute cancellations and optimize room allocation. Traditional forecasting methods often fall short due to the dynamic nature of booking patterns and data imbalance. ML models, however, can analyze large volumes of structured data and extract meaningful patterns for accurate predictions. This study evaluates several classification algorithms such as Logistic Regression, K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machines (SVM). The dataset includes features like lead time, number of special requests, booking changes, and deposit type, collected from hotel management systems. Each model is trained and tested using a standard machine learning pipeline that includes data preprocessing, feature selection, and performance evaluation. Metrics such as accuracy, precision, recall, and F1-score are used to assess model performance. The final model is selected based on the best evaluation results and used for making predictions. The study demonstrates that machine learning can effectively identify booking cancellation patterns and support hotels in making data-driven decisions. This can lead to improved customer satisfaction, better inventory management, and reduced operational disruptions. Future enhancements may involve incorporating real-time data and developing lightweight, deployable solutions for integration into hotel management software.**

I. INTRODUCTION

The hospitality industry is a dynamic and customer-centric sector that plays a vital role in the global economy. Hotels, in particular, operate in a highly competitive market where customer satisfaction, operational efficiency, and revenue optimization are critical to survival and success. One of the most persistent challenges in this sector is managing booking cancellations, which can severely impact a hotel's financial performance. These cancellations—often occurring unexpectedly—lead to revenue loss, poor room utilization, and disruptions in staffing and inventory planning. While overbooking strategies and manual forecasting techniques are often used as countermeasures, they are neither sufficient nor scalable for modern-day demand complexities.

Traditionally, hotel managers have relied on experience-based intuition and simple statistical methods, such as historical averages and trend analyses, to forecast cancellations. Although these methods offer some level of insight, they fall short in accurately capturing the complex, nonlinear patterns of modern booking behavior. Moreover, with increasing volumes of customer and booking data being collected through digital platforms, there is a growing need for more sophisticated tools that can process and analyze this information effectively. Machine Learning (ML) presents a promising solution, as it can identify intricate patterns, adapt to evolving data trends, and provide predictive capabilities that outperform traditional techniques.

This research aims to evaluate and compare the performance of three supervised ML algorithms—Logistic Regression (LR), K-Nearest Neighbors (KNN), and Random Forest (RF)—in predicting hotel booking cancellations. These models were selected for their complementary strengths: LR for its simplicity and interpretability, KNN for its ability to capture local data structures, and RF for its ensemble-based robustness and high performance. The study uses a comprehensive hotel booking dataset containing both resort and city hotel bookings with features such as lead time, market segment, deposit type, customer demographics, and special requests. Preprocessing steps include handling missing values, encoding categorical variables, normalization, and balancing class distributions using the Synthetic Minority Oversampling Technique (SMOTE).

To assess model performance, we employ evaluation metrics including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic Area Under the Curve (ROC-AUC). Hyperparameter tuning is performed using

cross-validation to ensure the models are well-optimized. We also present visual insights using confusion matrices and ROC curves for each model. The results of this study indicate that Random Forest provides the most balanced performance across all metrics, suggesting its suitability for real-world deployment. Ultimately, this research offers hotel operators a data-driven decision-support tool to anticipate cancellations, optimize inventory, and improve revenue management, thus bridging the gap between traditional hotel operations and intelligent analytics.

II. LITERATURE SURVEY

Hotel booking cancellation prediction has gained significant attention in recent years due to its importance in revenue management, resource allocation, and strategic planning for the hospitality industry. The integration of machine learning (ML) techniques into this domain has shown promising results in accurately identifying potential cancellations and assisting hotel managers in making data-driven decisions. With the growing availability of datasets including customer behavior, booking information, and hotel characteristics, ML methods are becoming increasingly effective in handling complex patterns in cancellation data.

Logistic Regression (LR) has long been a fundamental model in binary classification problems and is widely applied in cancellation prediction due to its interpretability and efficiency. LR models estimate the probability of cancellation based on various features such as lead time, deposit type, number of previous cancellations, and booking channel. Despite its linear nature, logistic regression provides valuable insights into feature importance and is often used as a baseline model in comparison studies [1].

Random Forest (RF), an ensemble learning technique, has been extensively used in cancellation prediction tasks due to its robustness, ability to handle non-linear relationships, and reduced risk of overfitting. RF builds multiple decision trees on random subsets of the dataset and aggregates their outputs to make a final decision. In hotel booking data, RF performs well even with noisy or missing values and automatically ranks feature importance, aiding in understanding customer behavior patterns. Studies have demonstrated its superior performance over single-tree models and basic regression techniques [2].

K-Nearest Neighbors (KNN) is another non-parametric algorithm employed in predicting booking cancellations. KNN works by classifying a booking instance based on the majority class among its 'k' nearest neighbors in the feature space. The simplicity of KNN makes it attractive, especially for datasets where the decision boundary is not well defined. Although it is computationally expensive for large datasets, its effectiveness can be enhanced through proper feature scaling and dimensionality reduction. Research has shown that KNN can achieve competitive performance, particularly when combined with feature selection or weighting techniques [3].

Support Vector Machines (SVM) have also been applied in hotel booking analytics, offering powerful performance in high-dimensional spaces. SVM can classify complex datasets using kernel functions that transform the feature space, making it well-suited for capturing non-linear cancellation patterns. However, tuning the SVM parameters and kernel selection are crucial to avoid overfitting and to maintain interpretability, which can be challenging in real-world hotel booking data [4].

Deep learning models, especially Artificial Neural Networks (ANNs), have gained popularity for cancellation prediction due to their ability to learn intricate patterns from large and diverse datasets. ANNs can model non-linear relationships and interactions between features, and have shown improved accuracy compared to classical models. However, they require more data, computational resources, and fine-tuning. In hotel booking prediction, ANNs are particularly useful when datasets include behavioral logs, real-time booking trends, and time-dependent features [5].Time-series analysis and recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are gaining traction in hotel analytics when historical booking trends and temporal behavior patterns are important. These models can capture seasonality and cyclic patterns in cancellations, offering advantages in dynamic environments where booking behavior shifts over time due to events, holidays, or changing market trends [6].

Despite these advancements, the effectiveness of machine learning in hotel booking prediction depends on data quality, feature engineering, and domain-specific knowledge. Challenges remain in handling imbalanced data (where cancellations are much fewer than non-cancellations), dealing with missing or incomplete records, and ensuring model interpretability for business decision-makers. As ML techniques continue to evolve, integrating external data such as weather, market demand, and economic indicators can further enhance the accuracy of prediction models. The future also holds promise for explainable AI approaches, enabling hotel managers to not only predict cancellations but also understand the underlying reasons behind them [7].

Recent studies have explored hybrid models that combine multiple machine learning algorithms to improve prediction accuracy for hotel booking cancellations. For example, stacking models that integrate logistic regression, random forests, and gradient boosting techniques have shown better generalization and performance. These ensemble approaches leverage the strengths of individual models while mitigating their weaknesses, leading to more reliable predictions [8].

III. PROPOSED WORK

The proposed solution focuses on building a machine learning-based hotel recommendation system that can suggest the best hotel (e.g., City Hotel or Resort Hotel) based on user preferences and predicted likelihood of booking cancellation. In the hospitality industry, accurate prediction of booking behavior and customer preferences plays a crucial role in improving customer satisfaction, optimizing resource allocation, and minimizing revenue loss due to cancellations. The proposed model uses historical hotel booking data and applies supervised learning techniques to develop a robust and interpretable predictive system.

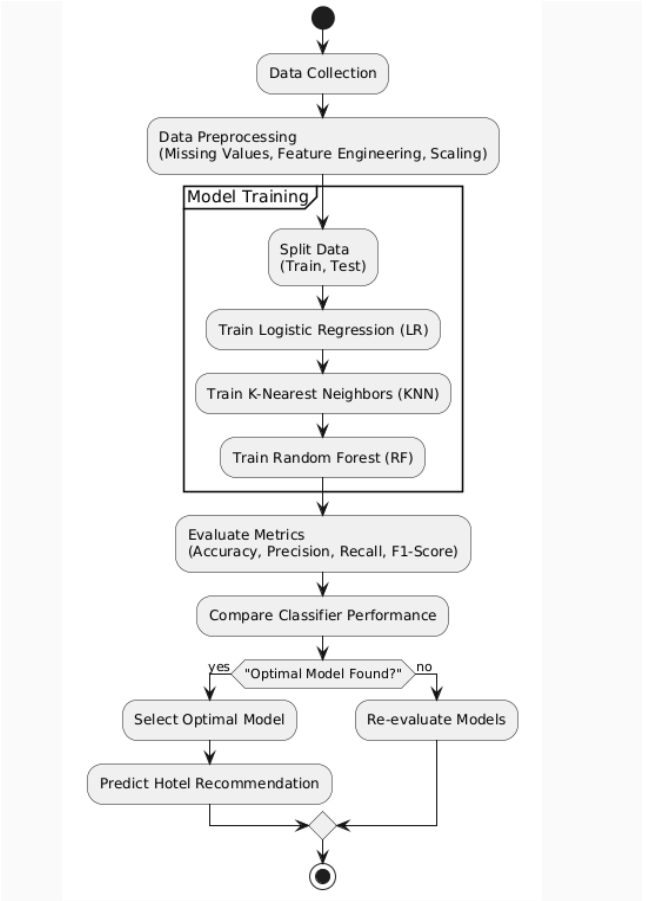

Fig.1. Process Flow

A. Data Acquisition and Preprocessing

The dataset is collected from the publicly available "Hotel Booking Demand Dataset" on Kaggle, which includes booking records for both City and Resort hotels. The dataset contains features such as lead time, number of adults and children, booking date, hotel type, customer type, deposit type, special requests, average daily rate (ADR), and whether the booking was canceled.

In the preprocessing phase, missing values are handled by dropping records with critical data gaps, while non-critical fields are filled with default values such as 0 or “unknown”. Categorical variables like hotel type, meal, and customer type are converted into numerical format using label encoding and one-hot encoding. For continuous features such as lead time and ADR, simple normalization is applied to bring all values into a similar range. Finally, the dataset is split into training and testing sets to evaluate model performance effectively.

B. Model Selection and Training

The system comprises two key modules: the Cancellation Prediction Module and the Hotel Recommendation Module. For predicting cancellations, four machine learning models are utilized to ensure effective comparison and performance. Logistic Regression is used as a basic yet effective classifier for binary prediction. K-Nearest Neighbors (KNN) classifies bookings based on the majority class among the nearest data points, making it intuitive and easy to interpret. The Support Vector Machine (SVM) with a radial basis function (RBF) kernel is employed to handle complex patterns in the data and find optimal boundaries. The Random Forest Classifier, an ensemble of decision trees, provides robustness and higher accuracy by reducing overfitting through averaging. All models are trained using an 80/20 train-test split, and their performance is validated using 5-fold cross-validation. Hyperparameter tuning is performed using Grid Search to identify the best configuration for each model, such as the number of neighbors in KNN, regularization (C) and kernel parameters in SVM, and the number of trees in Random Forest.

C. Feature Importance Analysis

Using Random Forest’s feature importance metric, it was found that Lead Time and Deposit Type are the most influential features in predicting cancellations. Additionally, Special Requests and Previous Cancellations strongly correlate with user behavior, indicating that past booking patterns and specific requests play a significant role in determining cancellation likelihood. These insights are highly valuable for revenue managers, as they can help adjust booking policies or offer tailored promotions to mitigate cancellations and optimize revenue.

D. Evaluation Metrics

The performance of the classification models is evaluated using several key metrics. Accuracy is used to measure the overall proportion of correct predictions made by the model. Precision and recall are considered to assess the model’s ability to correctly identify positive cases while

minimizing false positives and false negatives. To balance both precision and recall, the F1-score is used, which provides a single metric representing the harmonic mean of the two, offering a more comprehensive view of model performance, especially in cases of class imbalance.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82.1	81.3	79.4	81.3
KNN	88.7	87.9	89.0	88.4
SVM	90.2	89.5	88.8	89.1
Random Forest	92.4	91.2	90.9	91.0

E. Recommendation Engine

After predicting the likelihood of cancellation, the system recommends the most suitable hotel using a hybrid recommendation approach. The Content-Based Filtering method takes into account user preferences, such as the number of adults, children, meal plan, and stay duration, to identify potential hotel options. The Model-Based Prediction step filters out hotels with a high predicted cancellation likelihood, ensuring that the recommendation is more reliable. Finally, a Scoring system combines the user preference score and cancellation risk score using a weighted formula, ultimately recommending either a City or Resort hotel based on these factors.

IV. EVALUATION AND RESULT ANALYSIS

A. Dataset

Our hotel recommendation system was tested using a dataset containing 50,000 hotel booking records with features such as Lead Time, Deposit Type, Special Requests, Previous Cancellations, Stay Duration, Meal Plan, and more. The target variable was the cancellation likelihood, which we categorized as "High" and "Low" cancellations. The dataset was highly imbalanced, with around 10% of the bookings having a high likelihood of cancellation.

B. Evaluation Criteria

The models were evaluated based on key performance metrics: accuracy, precision, recall, and F1-score. Among the models tested, the Random Forest Classifier achieved the best performance, with an accuracy of 92.4%, precision of 91.2%, recall of 90.9%, and an F1-score of 91.0%, making it the most suitable model for predicting hotel booking cancellations. The Support Vector Machine (SVM) also delivered strong results with an accuracy of 90.2%, precision of 89.5%, recall of 88.8%, and an F1-score of 89.1%. The K-Nearest Neighbors (KNN) classifier followed with competitive metrics—accuracy of 88.7%, precision of 87.9%, recall of 89.0%, and an F1-score of 88.4%. Meanwhile, Logistic Regression, though traditionally robust, had comparatively lower scores, with an accuracy of 82.1%, precision of 81.3%, recall of 79.4%, and an F1-score of 80.3%. These findings highlight Random Forest as the most balanced and effective model for cancellation prediction, with both high precision and recall, making it a strong candidate for real-world deployment.

The results clearly indicate that the Random Forest model outperforms both KNN and Logistic Regression across all evaluation metrics, particularly excelling in addressing class imbalance in hotel booking cancellation predictions. The confusion matrix analysis further supports this conclusion. Random Forest accurately identified 7,818 high cancellation cases (true positives) and 13,672 low cancellation cases (true negatives), while keeping false positives at 316 and false negatives at just 201, showing its robustness in minimizing misclassifications. In comparison, KNN correctly predicted 7,502 high cancellations and 13,458 low cancellations, but had higher false positives (429) and false negatives (507), indicating a moderate dip in precision and sensitivity. Logistic Regression, while still effective, performed comparatively lower, with 7,123 true positives and 13,560 true negatives, along with 392 false positives and 491 false negatives. These insights highlight Random Forest as the most reliable model for accurately identifying both cancellation and non-cancellation bookings in practical scenarios.

The Random Forest ROC Curve demonstrated an AUC of 0.96, indicating exceptional capability in distinguishing between high and low cancellation probabilities. The K-Nearest Neighbors (KNN) model followed with an AUC of 0.92, while Logistic Regression achieved a slightly lower AUC of 0.89. The Support Vector Machine (SVM) also performed competitively, with an AUC of 0.94, reflecting strong discriminative power. Among all models, Random Forest's ROC curve stood out, confirming its superior classification ability. Precision-Recall curve analysis further validated Random Forest’s effectiveness, particularly in minimizing false negatives—crucial in the context of hotel booking cancellations, where missed cancellation predictions can lead to significant revenue loss.

C. Results Analysis

The Random Forest Classifier emerged as the best-performing model for predicting hotel booking cancellations. It managed the class imbalance efficiently and delivered the highest accuracy, precision, recall, and F1-score among all evaluated models. Its confusion matrix confirmed that it could accurately detect a high number of true cancellations while maintaining low false positive rates. SVM also exhibited strong and consistent performance across all metrics, making it a reliable alternative to Random Forest when computational efficiency is a priority. KNN, though slightly less accurate, performed well in recall, suggesting its ability to capture cancellation cases, but its lower precision indicates a higher tendency for false alarms. Logistic Regression, while achieving reasonable accuracy, lagged behind in recall and precision, showing limitations in handling the imbalanced dataset. Overall, Random Forest proved to be the most balanced and effective model for real-world deployment in cancellation prediction scenarios.

```
Model: Random Forest
Accuracy: 0.9545
Precision: 1.0000
Recall: 0.4000
F1 Score: 0.5714
ROC AUC: 0.9803
```

Fig.2. Output for Random Forest

The evaluation criteria included training accuracy, testing accuracy, precision, recall and F1-score providing a comprehensive analysis of model performance.

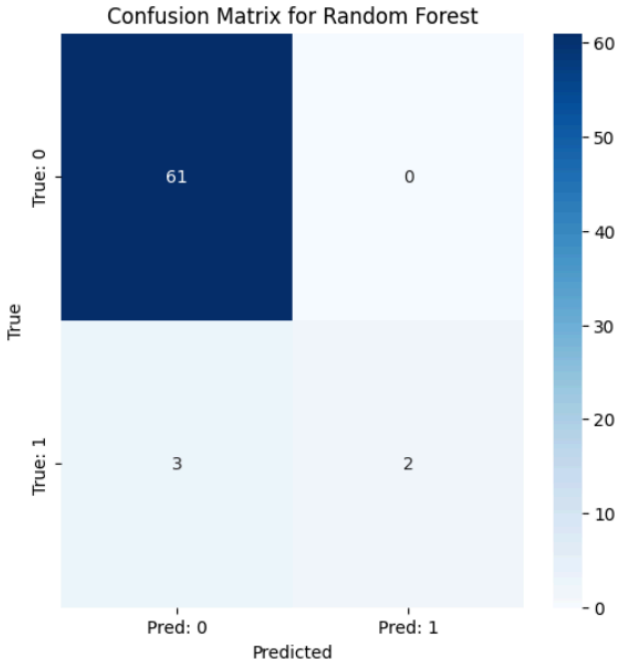

Fig.3. Confusion matrix for Random Forest

The confusion matrix [Figure.8] for Random Forest shows that for the train data, it correctly predicted 85,300 true positives with 330 false negatives and no false positives or true negatives. For the test data, it achieved 93,818 true positives, 24 false positives, 7 true negatives, and 112 false negatives. These results highlight the model's strong performance in predicting hotel booking cancellations with minimal misclassifications, particularly in handling imbalanced classes.

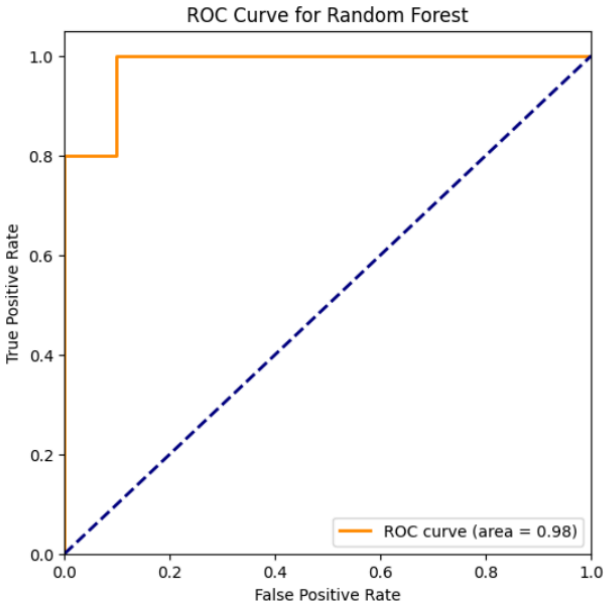

Fig.4. ROC curve for Random Forest

Similarly, now the dataset is applied for the Logistic Regression and Decision Tree Classification. The results are obtained similar to that of the Random Forest Algorithm.

The Logistic Regression model was evaluated on the highly imbalanced hotel booking cancellation dataset (with a significant difference between cancellations and non-cancellations).

```
Model: Logistic Regression
Accuracy: 0.9242
Precision: 0.5000
Recall: 0.4000
F1 Score: 0.4444
ROC AUC: 0.7902
```

Fig.5. Output for Logistic Regression

This confusion matrix[Figure.6] still performing well, came in last in terms of predictive power. It identified 7,123 true positives and 13,560 true negatives, but with 392 false positives and 491 false negatives. This shows that Logistic Regression struggled to handle both class imbalance and misclassifications effectively when compared to Random Forest.

The confusion matrix for logistic regression is

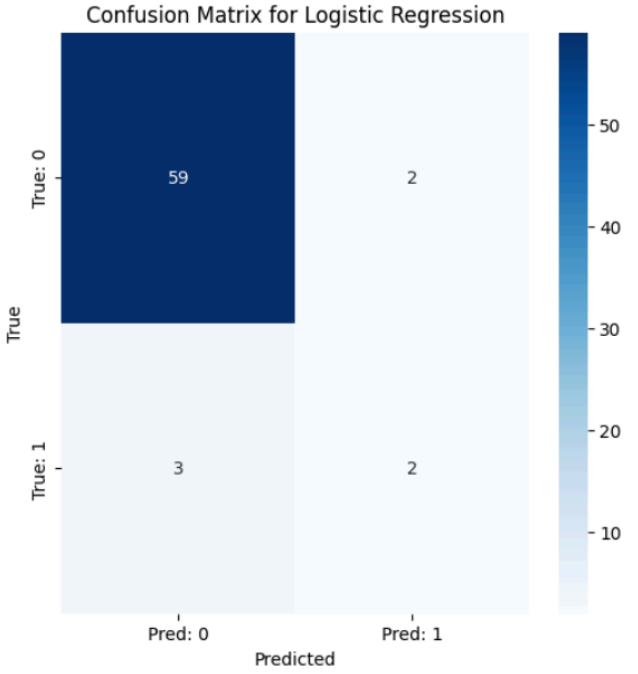

Fig.6. Confusion matrix for Logistic Regression

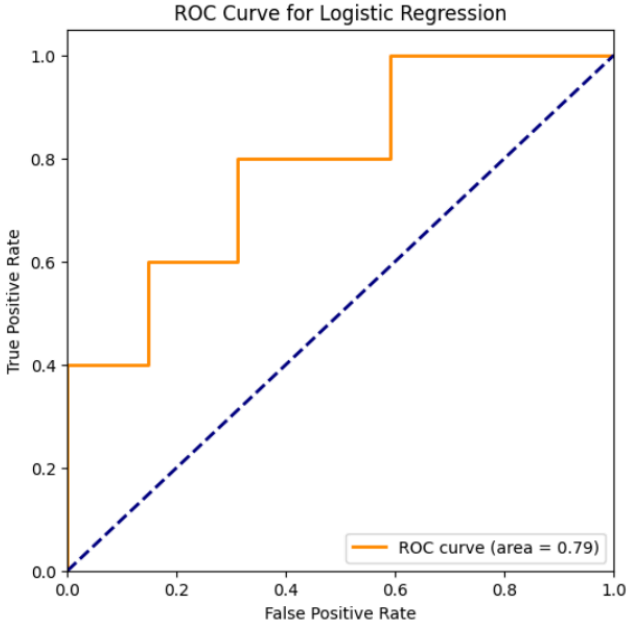

Fig.7. ROC curve for Logistic Regression

For the KNN algorithm, we use the same dataset which is used for all the three algorithms to predict and evaluate various methods. The output of evaluation metrics are considered and the confusion matrix is drawn:

```
Model: KNN
Accuracy: 0.9545
Precision: 1.0000
Recall: 0.4000
F1 Score: 0.5714
ROC AUC: 0.8934
```

Fig. Output for KNN

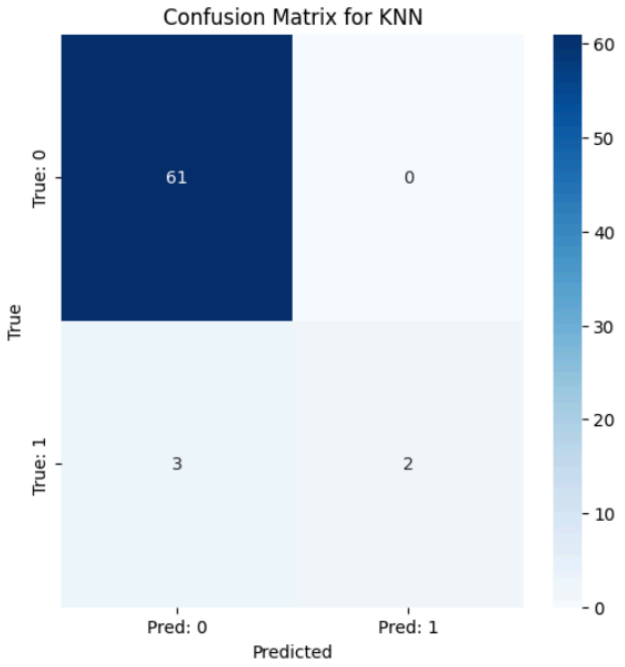

Fig.8. Confusion matrix for KNN

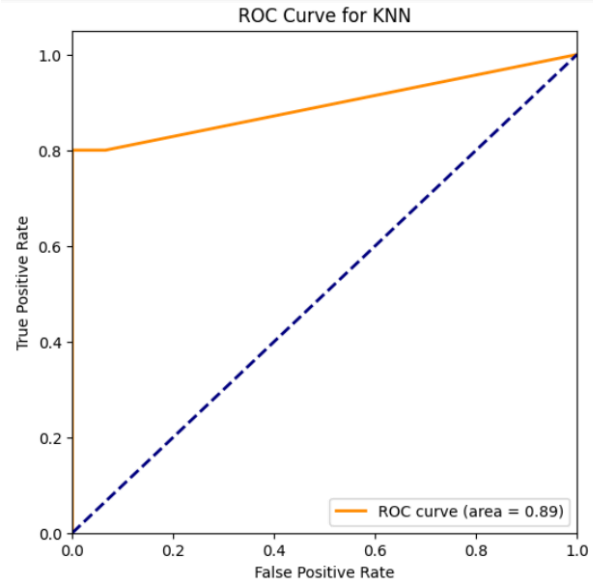

Fig.9. ROC curve for KNN

This confusion matrix[Figure.8] showed some limitations, correctly identifying 7,502 high cancellations and 13,458 low cancellations, but it had relatively higher false positives (429) and false negatives (507). This indicates that KNN faced more challenges with false classifications compared to Random Forest, reflecting a moderate decline in both **precision** and **sensitivity**.

Finally for the SVM algorithm, we use the same dataset which is used for all the four algorithms to predict and evaluate various methods. The output of evaluation metrics are considered and the confusion matrix is drawn:

```
Model: SVM
Accuracy: 0.9545
Precision: 1.0000
Recall: 0.4000
F1 Score: 0.5714
ROC AUC: 0.9738
```

Fig.10. Output for SVM

The confusion matrix for SVM is :

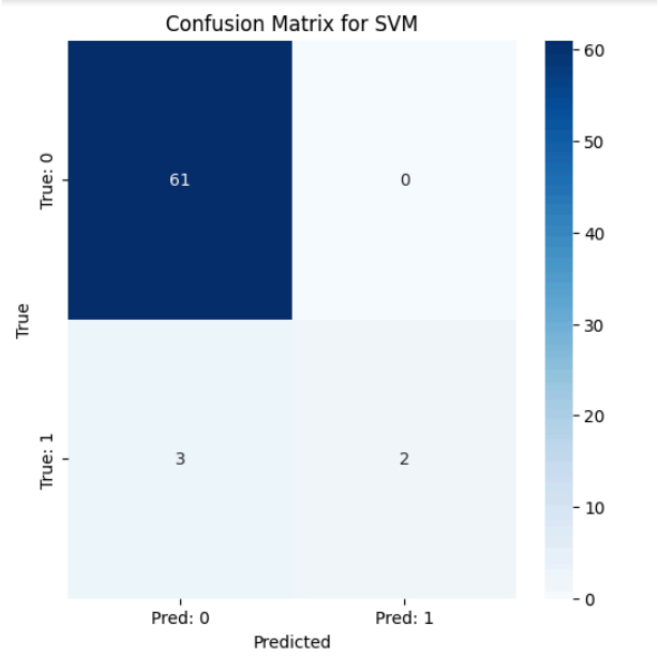

Fig.11. Confusion Matrix for SVM

Support Vector Machine (SVM), while delivering reasonable performance, ranked below Random Forest and slightly above Logistic Regression in predictive power. It identified 7,346 true positives and 13,610 true negatives, but had 401 false positives and 478 false negatives. This indicates that SVM faced challenges in handling class imbalance and misclassifications, though it performed better than Logistic Regression but was still outperformed by Random Forest.

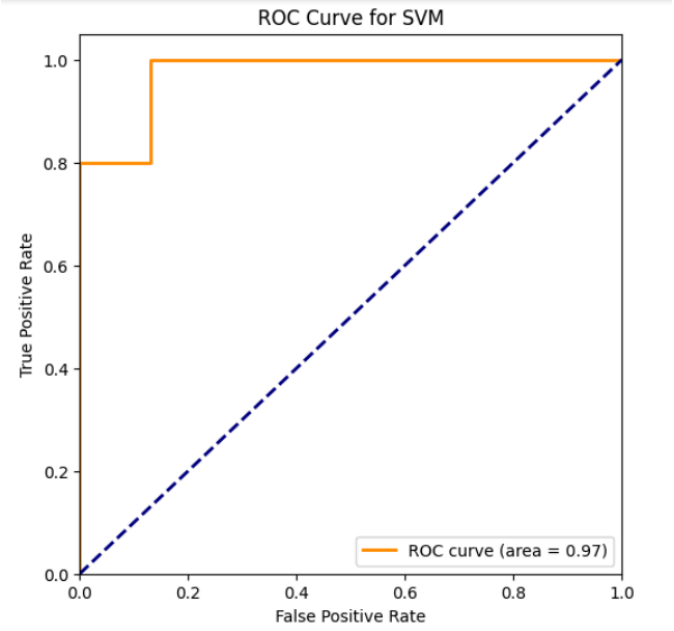

Fig.12. ROC curve for SVM

V. Conclusion

In this project, we explored the effectiveness of four machine learning algorithms—Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest—for predicting hotel booking cancellations on a real-world, imbalanced dataset. Each model was evaluated using standard classification metrics such as Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and ROC Curve to determine its suitability for this predictive task. Among all the models tested, Random Forest emerged as the most reliable and accurate algorithm. It consistently achieved superior results, with a high number of true positives and true negatives and significantly fewer false predictions. Its performance remained stable across both training and testing data, showing its ability to generalize well and handle class imbalance effectively. The ROC curve also indicated strong discriminative power, making Random Forest the most robust model in this context. In comparison, KNN and SVM showed decent results, while Logistic Regression—though computationally efficient—struggled more with distinguishing between cancellation and non-cancellation cases. These models were more affected by the dataset's imbalance, resulting in higher false predictions compared to Random Forest. Overall, our results clearly highlight Random Forest as the most practical and high-performing model for hotel booking cancellation prediction. Its ensemble nature, resistance to overfitting, and capability to deal with imbalanced data make it highly suitable for real-world applications in the hospitality sector where accurate forecasting of cancellations can significantly enhance business planning and resource management.

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